DOCUMENT RESUME

ED 237 533 TM 830 783

AUTHOR	Lord, Frederic M.
TITLE	Estimating the Imputed Social Cost of Errors of Measurement.
INSTITUTION	Educational Testing Service, Princeton, N.J.
SPONS AGENCY	Office of Naval Research, Arlington, Va. Personnel and Training Research Programs Office.
REPORT NO	ETS-RR-83-33-ONR
PUB DATE	Oct 83
CONTRACT	N00014-80-C-0402
NOTE	40p.
PUB TYPE	Reports - Research/Technical (143)
EDRS PRICE	MF01/PC02 Plus Postage.
DESCRIPTORS	Cutting Scores; Decision Making; *Error of Measurement; *Estimation (Mathematics); *Latent Trait Theory; Measurement Techniques; Research Methodology; Scores; Social Problems; *Test Construction; *Testing Problems; Test Items
IDENTIFIERS	*Loss Function

ABSTRACT

If a loss function is available specifying the social cost of an error of measurement in the score on a unidimensional test, an asymptotic method, based on item response theory, is developed for optimal test design for a specified target population of examinees. Since in the real world such loss functions are not available, it is more useful to reverse this process; thus a method is developed for finding the loss function for which a given test is an optimally designed test for the target population. An illustrative application is presented for one operational test. (Author)

****
* Reproductions supplied by EDRS are the best that can be made *
* from the original document. *
****

ED237533

RR-83-33-ONR

U.S. DEPARTMENT OF EDUCATION
NATIONAL INSTITUTE OF EDUCATION
EDUCATIONAL RESOURCES INFORMATION CENTER (ERIC)
X This document has been reproduced as received from the person or organization originating it.
☐ Minor changes have been made to improve reproduction quality.
• Points of view or opinions stated in this document do not necessarily represent official NIE position or policy.

ESTIMATING THE IMPUTED SOCIAL COST OF ERRORS OF MEASUREMENT

Frederic M. Lord

This research was sponsored in part by the
Personnel and Training Research Programs
Psychological Sciences Division
Office of Naval Research, under
Contract No. N00014-80-C-0402

Contract Authority Identification Number
NR No. 150-453

Frederic M. Lord, Principal Investigator

Educational Testing Service

Princeton, New Jersey

October 1983

Reproduction in whole or in part is permitted for any purpose of the United States Government.

Approved for public release; distribution unlimited.

TM830783

ESTIMATING THE IMPUTED SOCIAL COST OF ERRORS OF MEASUREMENT

Frederic M. Lord

This research was sponsored in part by the
Personnel and Training Research Programs
Psychological Sciences Division
Office of Naval Research, under
Contract No. N00014-80-C-0402

Contract Authority Identification Number
NR No. 150-453

Frederic M. Lord, Principal Investigator

Educational Testing Service

Princeton, New Jersey

October 1983

Reproduction in whole or in part is permitted
for any purpose of the United States Government.

Approved for public release; distribution
unlimited.

UNCLASSIFIED

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) Estimating the Imputed Social Cost of Errors of Measurement		5. TYPE OF REPORT & PERIOD COVERED Technical Report
		6. PERFORMING ORG. REPORT NUMBER RR-83-33-ONR
7. AUTHOR(s) Frederic M. Lord		8. CONTRACT OR GRANT NUMBER(s) N00014-80-C-0402
9. PERFORMING ORGANIZATION NAME AND ADDRESS Educational Testing Service Princeton, New Jersey 08541		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS NR-150-453
11. CONTROLLING OFFICE NAME AND ADDRESS Personnel and Training Research Programs Office of Naval Research Arlington, Virginia 22217		12. REPORT DATE October 1983 13. NUMBER OF PAGES 25
14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office)		15. SECURITY CLASS. (of this report) Unclassified 15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Item Response Theory, Decision Theory, Test Design, Loss Function, Information Function, Item Selection

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

If a loss function is available specifying the social cost of an error of measurement in the score on a unidimensional test, an asymptotic method, based on item response theory, is developed for optimal test design for a specified target population of examinees. Since in the real world such loss functions are not available, it is more useful to reverse this process; thus a method is developed for finding the loss function for which a given test is an optimally designed test for the target population. An illustrative application is presented for one operational test.

DD FORM JAN 73 1473 EDITION OF 1 NOV 65 IS OBSOLETE

S/N 0102-LF-014-6601

UNCLASSIFIED

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

Abstract

If a loss function is available specifying the social cost of an error of measurement in the score on a unidimensional test, an asymptotic method, based on item response theory, is developed for optimal test design for a specified target population of examinees. Since in the real world such loss functions are not available, it is more useful to reverse this process; thus a method is developed for finding the loss function for which a given test is an optimally designed test for the target population. An illustrative application is presented for one operational test.

Estimating the Imputed Social Cost of Errors of Measurement*

For a unidimensional test, the error of measurement is the difference between the examinee's true ability θ and the estimate of this ability represented by the examinee's test score $\hat{\theta}$. Since discrepancies between $\hat{\theta}$ and θ may lead to erroneous decisions about the examinee (misclassification, erroneous acceptance or rejection), there is an expected social cost associated with any pair of values $(\hat{\theta},\theta)$. This cost is given by some loss function $L(\hat{\theta},\theta)$.

The obvious problem, here called Problem 1, is: Given the loss function $L(\hat{\theta},\theta)$, how can we build an (optimal) n-item test that will minimize the expected loss over a specified target population of examinees, subject to certain constraints on the statistical characteristics of the items in the available item pool? Using item response theory, [Lord, 1980; Hulin, Drasgow, and Parsons, 1983], a solution of this problem will be given here for a unidimensional test.

Unfortunately, in practice it is unlikely that $L(\hat{\theta},\theta)$ will be known to the test designer. Something of practical value can still be salvaged, however, if we can deal with Problem 2: Given an existing unidimensional test and a specified target population of examinees, find the loss function $L(\hat{\theta},\theta)$ for which this test is an optimally designed test. If the

---

*The theoretical work in Sections 1-4 was supported by contract N00014-80-C-0402, project designation NR 150-453 between the Office of Naval Research and Educational Testing Service. The empirical work, using ETS data, was supported by ETS funds. The writer is very much indebted to Martha L. Stocking, who was responsible for obtaining the empirical results reported in Section 5.

loss function found for Problem 2 does not agree with our intuitive notions as to what is appropriate, we will probably redesign future test forms to avoid this discrepancy.

In order to solve Problem 2, it is necessary first to solve Problem 1; this is done in the first section. The solution to Problem 2 is outlined in the second section. Invariance under transformations of the ability scale is discussed in Section 3. In Section 4, a method for estimating the ability distribution of the target population is discussed. An illustrative application to an actual test is given in Section 5. The final section briefly discusses some implications for optimal test design.

It is assumed here that all item parameters have been determined by pretesting to sufficient accuracy so that they can be treated as known. The illustrative example and some of the discussion are based on the three-parameter logistic model of the item response function (with which the reader is assumed to be familiar), but the proofs of the main results are much more general. The examinee's actual score $\hat{\theta}$ is assumed to be the maximum likelihood estimate of θ, calculated from the examinee's responses to the n test items.

1. Minimizing Expected Loss

For a group of examinees at a given ability level θ, the conditional expected loss is by definition

$$\mathcal{E}(L|\theta) = \int_{-\infty}^{\infty} L(\hat{\theta},\theta)\, \phi(\hat{\theta}|\theta)\, d\hat{\theta} \qquad (1)$$

where $\phi(\hat{\theta}|\theta)$ is the conditional distribution of $\hat{\theta}$ and $\mathcal{E}$ denotes expectation. If the distribution of ability θ in the target population is denoted by $g(\theta)$, then the overall (unconditional) expected loss is by definition

$$\mathcal{E}(L) = \int_{-\infty}^{\infty} \mathcal{E}(L|\theta)\, g(\theta)\, d\theta \quad . \qquad (2)$$

This is the quantity to be minimized by optimal test design.

Loss Function

Certain reasonable assumptions will be made about the loss function:

1. $L(\theta,\theta) = 0$ (because when $\hat{\theta} = \theta$, there is no error of measurement and hence no loss due to error of measurement).
2. When $\hat{\theta} \neq \theta$, $L(\hat{\theta},\theta) > 0$.
3. When $\hat{\theta}$ is near θ, the loss function and its first two derivatives with respect to $\hat{\theta}$ are continuous, the third derivative is bounded. [These conditions will guarantee the convergence of (3).]
4. The loss function does not change too sharply with changes in θ (as will be discussed later).

For fixed θ, expand $L(\hat{\theta},\theta)$ in powers of $\hat{\theta} - \theta$, obtaining

$$L(\hat{\theta},\theta) = L(\theta,\theta) + (\hat{\theta} - \theta)L'(\theta,\theta) + \frac{1}{2}(\hat{\theta} - \theta)^2 L''(\theta,\theta) + \ldots$$

where $L'(\theta,\theta)$ and $L''(\theta,\theta)$ denote successive derivatives of $L(\hat{\theta},\theta)$ with respect to $\hat{\theta}$, evaluated at $\hat{\theta} = \theta$. The first term vanishes because there is no error of measurement when $\hat{\theta} = \theta$. The second term vanishes because for fixed θ, $L(\hat{\theta},\theta)$ has a minimum at $\hat{\theta} = \theta$. Consequently,

$$L(\hat{\theta},\theta) = \frac{1}{2}(\hat{\theta} - \theta)^2 L''(\theta,\theta) \text{ plus higher order terms.} \qquad (3)$$

Higher powers of $(\hat{\theta} - \theta)$ can be neglected if n is not too small, since $\hat{\theta} \to \theta$ in probability as $n \to \infty$ [Lord, 1980, p. 59].

When (3) is substituted into (1), $L''(\theta,\theta)$ comes out from under the integration sign. It is then apparent that asymptotically (that is, for large n)

$$\mathcal{E}(L|\theta) = \frac{1}{2} L''(\theta,\theta) \operatorname{Var}(\hat{\theta}|\theta) \quad . \qquad (4)$$

In item response theory, the asymptotic (conditional) variance of $\hat{\theta}$ is the reciprocal of the test information function $I(\theta)$ [Lord, 1980, Section 5.3]. Thus we shall rewrite the expected loss (2) as

$$\mathcal{E}(L) = \frac{1}{2} \int_{-\infty}^{\infty} \frac{L''(\theta,\theta)\, g(\theta)}{I(\theta)}\, d\theta \quad . \qquad (5)$$

Information Function

The item response function $P_i \equiv P_i(\theta)$ is the probability of a correct response to item i by a randomly chosen examinee at ability level θ. The information function is

$$I(\theta) = \frac{1}{\mathrm{Var}(\hat{\theta}|\theta)} = \sum_{i=1}^{n} \frac{P_i'^2}{P_i Q_i} \qquad (6)$$

where $Q_i \equiv 1 - P_i$ and $P_i' \equiv dP_i/d\theta$.

Ordinarily P_i depends on an item difficulty parameter b_i . Furthermore, b_i is typically simply a translation parameter: it affects P_i only through the difference $\theta - b_i$. In this standard situation, b_i also affects P_i' only through the difference $\theta - b_i$. Thus the area under any function F of P_i and P_i' over the whole range of θ

$$\int_{-\infty}^{\infty} F(\theta - b_i)\, d\theta = \int_{-\infty}^{\infty} F(\theta)\, d\theta$$

is independent of b_i . The area under the test information function thus does not depend on b_i in these typical models, which will be assumed here.

In the special case where $P_i(\theta)$ is the three-parameter logistic function

$$P_i(\theta) = c_i + \frac{1 - c_i}{1 + \exp[-1.7a_i(\theta - b_i)]} \quad , \qquad (7)$$

we have

$$P_i' = \frac{1.7a_i}{1 - c_i} Q_i(P_i - c_i)$$

and

$$\int_{-\infty}^{\infty} I(\theta)\, d\theta = \int_{-\infty}^{\infty} \sum_i \frac{P_i'^2}{P_i Q_i}\, d\theta \equiv \sum_i \int_{\infty}^{\infty} \frac{P_i'}{P_i Q_i} \frac{dP_i}{d\theta}\, d\theta = \sum_i \int_{c_i}^{1} \frac{P_i'}{P_i Q_i}\, dP_i$$

$$= \sum_i \frac{1.7a_i}{1 - c_i} \int_{c_i}^{1} \left(1 - \frac{c_i}{P_i}\right) dP_i = \sum_i \frac{1.7a_i}{1 - c_i} \left[P_i - c_i \log P_i\right]_{c_i}^{1}$$

$$= \sum_{i=1}^{n} \frac{1.7a_i}{1 - c_i} (1 - c_i + c_i \log c_i) \quad . \qquad (8)$$

This area does not depend on b_i .

Test Constraints

There are always constraints on the availability of items for test construction. Item writers can control to a considerable extent the difficulty level of the items they write. The discriminating power of the available items, however, can ordinarily be increased only by writing more items and then discarding a larger percentage of the items written--an expensive procedure.

It will be assumed here that the test developer has available an unlimited pool of items at whatever difficulty levels he or she may specify. The items in the pool have already been pretested; faulty items, especially those with low discriminating power, have already been discarded. The test developer is to build parallel forms of a test from the item pool, selecting items only on the basis of their difficulty b_i ,

so that each parallel form has the same distribution of b_i . Items cannot be selected on the basis of their discriminating power, since all items not discarded after pretesting must eventually be used. In the actual test produced, the frequency distribution of other item parameters, such as item discriminating power, is to be the same as in the total pool of pretested items. It will be assumed here that in the item pool the distribution of other item parameters is independent of the item difficulty b_i . This assumption should be checked empirically for any practical application.

This assumption may fail to hold because of the essential nature of the test items; often it also fails to hold simply because pretest item-test biserials have been used instead of the IRT discrimination parameter a_i to exclude poorly discriminating items from the available item pool. When item-test biserials are used in this way for multiple-choice items, the harder the item, the higher the a_i parameter must be for the item to escape exclusion from the item pool. This is true because among items with identical a_i , the more guessing the lower the item-test biserial.

It follows from these assumptions that the total area under the test information function is fixed. The task of the test developer is to minimize $\delta(L)$ by choice of b_i ($i = 1,2,\ldots,n$); no other relevant variables are available to the test developer for achieving this minimization.

Minimization

By the Cauchy inequality,

$$\int \frac{L''g}{I} \cdot \int I \geq \left(\int \sqrt{L''g} \right)^2 \quad .$$

Here, the first integral is twice the expected loss (5) written in abbreviated notation. Transposing, we have

$$\int \frac{L''g}{I} \geq \left(\int \sqrt{L''g} \right)^2 \div \int I \quad . \tag{9}$$

In Problem 1, $L''(\hat{\theta},\theta)$ and $g(\theta)$ are known; furthermore $\int_{-\infty}^{\infty} I(\theta)\, d\theta$ is fixed by the reasoning of the last two subsections. It follows that if there is an $I(\theta)$ such that equality holds in (9), then this is the $I(\theta)$ that minimizes the expected loss (5). Equality will hold in (9) provided

$$I(\theta) \text{ is proportional to } \sqrt{L''(\theta,\theta)\, g(\theta)} \quad .$$

Monetary Units

The loss function $L(\hat{\theta},\theta)$ is necessarily expressed in terms of some arbitrary unit (dollar, peso, ...). It may be convenient to choose this unit so that the area under $\sqrt{[L''(\theta,\theta)\, g(\theta)]}$ is equal to $\int_{-\infty}^{\infty} I(\theta)\, d\theta$, this last being a known and fixed quantity determined by n and by the item parameters, excluding the b_i, of the item pool. Once this choice of unit has been made, the expected loss will be minimized if the test developer can build a test with

$$I(\theta) = \sqrt{L''(\hat{\theta},\theta)\, g(\theta)} \quad . \tag{10}$$

Building the Test

Birnbaum [1968, Section 20.6] suggested an effective cut-and-try method for building a test having (approximately) a prespecified 'target' information function. The method is outlined in Lord [1980, Section 5 4]. The method follows easily from the fact that the test information function is simply a sum of the information functions $(P_i'^2/P_iQ_i)$ of the items included in the test.

The method is effective provided the target information curve is not too irregular and does not vary too rapidly as a function of θ. The results obtained here hold under this condition. If the target curve is too irregular, it will not be possible to build a test having the desired information function by selecting items on b_i from the available item pool.

Practical Procedure (Summary)

Given $L(\hat{\theta},\theta)$ and $g(\theta)$, to build k parallel test forms of length n that approximately minimize the expected loss:

1. Plot a_i and c_i against b_i to verify that the distribution of a_i and c_i in the item pool is approximately the same at all levels of b_i, as assumed in the subsection titled Test Constraints.
2. Compute

$$\int_{-\infty}^{\infty} I(\theta)\, d\theta = \frac{n}{M} \sum_{i=1}^{M} \int_{-\infty}^{\infty} \frac{P_i'^2}{P_iQ_i}\, d\theta$$

where M is the number of items in a large item pool. Note that this integral does not depend on the distribution of b_i in the pool.

3. Choose monetary units so that

$$\int_{-\infty}^{\infty} \sqrt{[L''(\theta,\theta)\ g(\theta)]}\ d\theta$$

is equal to

$$k \int_{-\infty}^{\infty} I(\theta)\ d\theta$$

for some integer k.

4. Selecting items only on their b_i, use Birnbaum's method to select a pool of nk items such that the sum of the nk item information functions is approximately equal to $\sqrt{[L''(\theta,\theta)\ g(\theta)]}$.

5. Divide the nk selected items into k test forms of n items each, all approximately parallel to each other.

2. The Loss Function for Which a Given Test Is an Optimal Test

If a given test is an optimal test, then (10) holds and

$$L''(\theta,\theta) = \frac{I^2(\theta)}{g(\theta)} \quad . \tag{11}$$

Consequently, the loss function is given approximately by (3) and (11):

$$L(\hat{\theta},\theta) = \frac{1}{2}\,\frac{I^2(\theta)}{g(\theta)}\,(\hat{\theta} - \theta)^2 \quad . \tag{12}$$

For fixed θ, this is the equation of a parabola. When n is not too small, $\hat{\theta}$ will be close to θ and (12) will provide an adequate approximation to the loss function for those values of $\hat{\theta}$ that are likely to be observed. For $\hat{\theta}$ close to θ, the desired loss function can be computed from (12) for any given test, provided $g(\theta)$ is specified.

3. Transformation of the Score Scale

Loss functions have an invariance property that is important in dealing with problems of test design. Consider the social cost in dollars of an error of measurement at a given ability level. If the error of measurement (the discrepancy between the actual test score and the true ability of which it is an estimate) is specified as a multiple of its standard error, asymptotically (for large n) the loss in dollars will be the same no matter what scale is used for measuring ability.

Instead of using the θ scale of ability, suppose we use the number-right true-score scale, given by the monotonic continuous transformation

$$\xi = \sum_{i=1}^{n} P_i(\theta) \quad . \tag{13}$$

The examinee's obtained score should now be taken to be

$$\hat{\xi} = \sum_{i=1}^{n} P_i(\hat{\theta}) \quad . \tag{14}$$

(Note that we need to use here the maximum likelihood estimator of ξ defined by (14), not the examinee's number of right answers.) If $\hat{\theta}$ differs from θ by K times S.E.$(\hat{\theta}|\theta)$, then, asymptotically, $\hat{\xi}$ will differ from ξ by K times S.E.$(\hat{\xi}|\xi)$. Asymptotically, K[S.E.$(\hat{\theta}|\theta)$] is actually the same error of measurement on the θ scale as K[S.E.$(\hat{\xi}|\xi)$] is on the ξ scale; thus the social consequences of this error will be the same regardless of the scale used.

Let $\theta(\xi)$ denote the inverse of transformation (13). Expressed on the ξ scale, the loss function (12) becomes

$$L_{\xi}(\hat{\xi},\xi) = \frac{1}{2} \frac{I^2[\theta(\xi)]}{g[\theta(\xi)]} [\theta(\hat{\xi}) - \theta(\xi)]^2$$

where $g(\ )$ and $I(\ )$ denote the same functions as previously. This equation could be used as it stands, but for reasons of symmetry, it may be preferable to expand it for fixed ξ in powers of $\hat{\xi} - \xi$. The result is found to be

$$L_{\xi}(\hat{\xi},\xi) = \frac{1}{2} \frac{I^2[\theta(\xi)]}{g[\theta(\xi)]} \left[\frac{d\theta(\xi)}{d\xi} \right]^2 (\hat{\xi} - \xi)^2 . \qquad (15)$$

Equation (15) is used here to represent the loss function when the obtained score is $\hat{\xi}$ rather than $\hat{\theta}$. This transformation has an advantage for presenting experimental results, since the number-right score scale is more familiar to us than the θ scale.

Note again that the actual monetary loss is the same regardless of the scale against which it is plotted. This invariance makes the loss function much more useful for guiding test design than the information function. Expressed on the θ scale, the test information function for θ is typically a bell-shaped curve; expressed on the ξ scale, the test information function for ξ is necessarily a U-shaped curve [Lord, 1980, Chapter 6]. This lack of invariance makes it difficult to use the test information function as a convincing basis for test design.

4. Estimating the True $g(\theta)$

By its definition, expected loss (2) requires specification of the distribution θ in the target population. It is important to note that the distribution of $\hat{\theta}$ in the target population is not an adequare estimate of $g(\theta)$, the true distribution of θ. The reason is that $\hat{\theta}$ contains errors of measurement and thus has a larger variance than θ. Since $g(\theta)$ appears in the denominator of (12), it is particularly important to estimate $g(\theta)$ as accurately as possible.

To obtain the numerical results of Section 5, the true distribution of number-right true score (13), here denoted by $f(\xi)$, was estimated by Method 20 [Lord, 1980, Chapter 16]. Since ξ is necessarily $\geq \Sigma_i P_i(-\infty)$, an estimated lower limit for ξ was set at $\Sigma_i \hat{c}_i$, where $\hat{c}_i$ represents the estimated c parameter of item i. For purposes of Section 5 all

item parameters were estimated under the three-parameter logistic model (7) by the computer program LOGIST [Note 1].

The required estimate of $g(\theta)$ for the target population was obtained from the Method 20 estimate of $f(\xi)$ by the relation

$$g(\theta) = f(\xi) \frac{d\xi}{d\theta} \quad . \tag{16}$$

The derivative in (16) is the derivative of (13), estimated in practice by computing $\Sigma_i P_i'(\theta)$ from estimated item parameters.

5. Illustrative Example

A representative sample of 19,949 examinees tested in 1981-82 was obtained for the Sentence Sense test in Form 3EJP of the New Jersey College Basic Skills Placement Test. This competency test consists of 35 four-choice items requiring the examinee to distinguish correct from incorrect English expression. The test is used primarily to assign certain entering college students to remedial English classes.

The item responses of all 19,949 examinees were analyzed, using LOGIST to estimate the item parameters of all items in the test. The true distribution of θ for the target population was estimated as described in Section 4 (for this purpose, a response chosen at random from the four choices was supplied wherever an examinee failed to respond to an item). The test information function (6) was calculated from the estimated item parameters. Finally, the loss function for which the test is an optimally designed test was estimated by (12).

Figure 1 shows the actual distribution of number-right scores (frequency polygon), the number-right true-score distribution estimated by Method 20 (solid curve), and the corresponding fitted distribution of (observed) number-right scores (dotted curve). The modal score is 31 right answers out of a possible 35. The chi square between observed and fitted number-right score distributions is at the 86th percentile of the chi square distribution with 18 degrees of freedom. In view of the large sample size (N = 19,949), this seems an adequate fit, as in indeed suggested visually by the agreement shown in Figure 1.

The estimated loss function (12) for which the test is an optimally designed test is plotted in Figure 2 against the θ and $\hat{\theta}$ Scales. The direction of the $\hat{\theta}$ scale is reversed from the conventional direction in order to improve visibility. Loss is shown on the vertical scale. In this and the next figure, the parabola for any given θ is drawn only for $\hat{\theta}$ values within two standard errors of the true θ .

The figure shows that the Sentence Sense test is built as if it were important to measure accurately at high ability levels as well as at low ability levels. Clearly, this is not appropriate for a competency test--the test should assign high losses to errors of measurement at low ability levels but <u>not</u> at high ability levels. The more difficult items in the test should be replaced by easier items.

The estimated loss function (15) for which the test is an optimally designed test is plotted in Figure 3 against number-right true score and

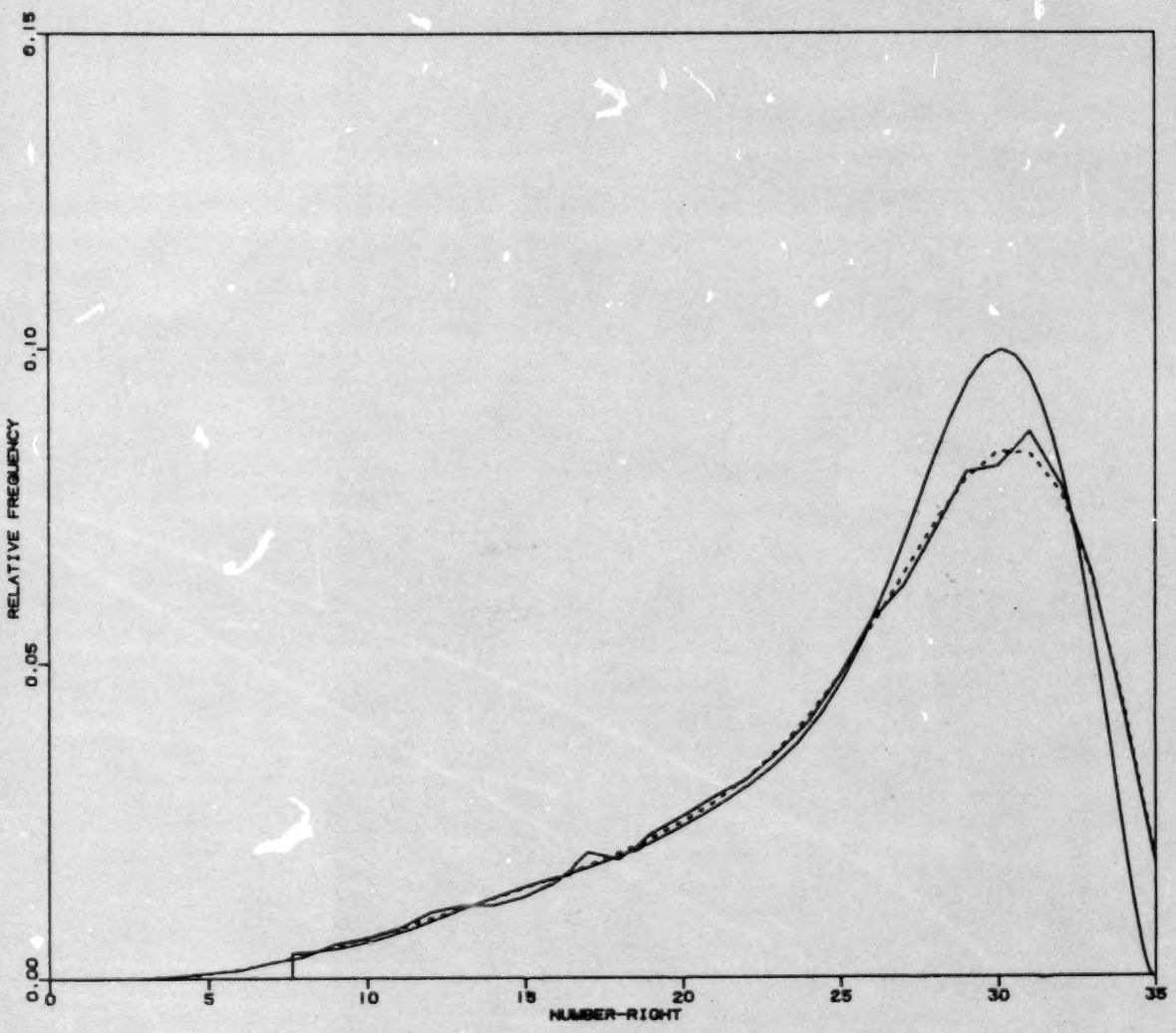

Figure 1. Frequncy distributions of true and observed number-right scores for NJCBSPT Sentence Sense, Form 3EJP, N = 19949 .

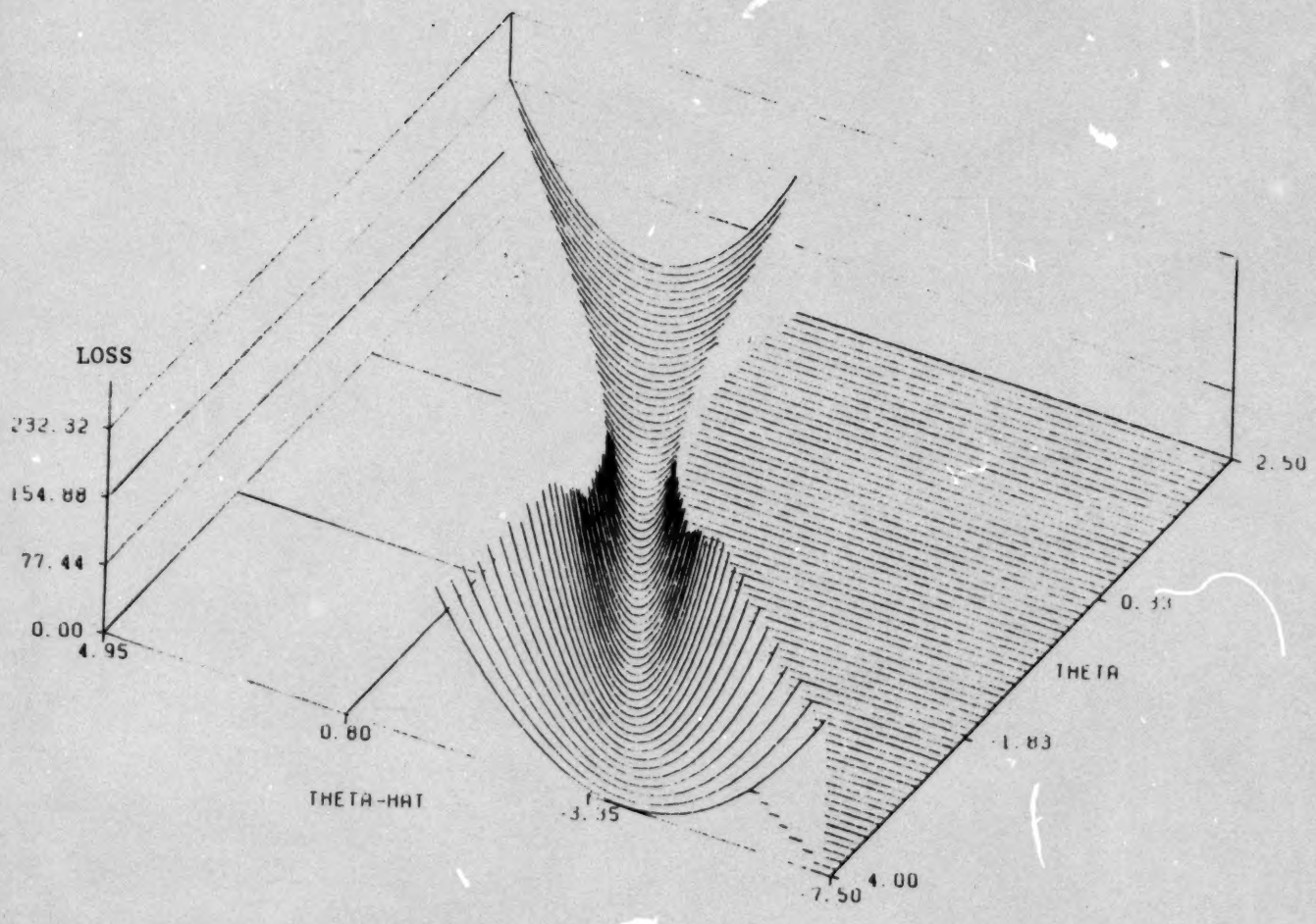

Figure 2. Loss function for NJBSCPT, JEJP, Sentence Sense, N = 19949 .

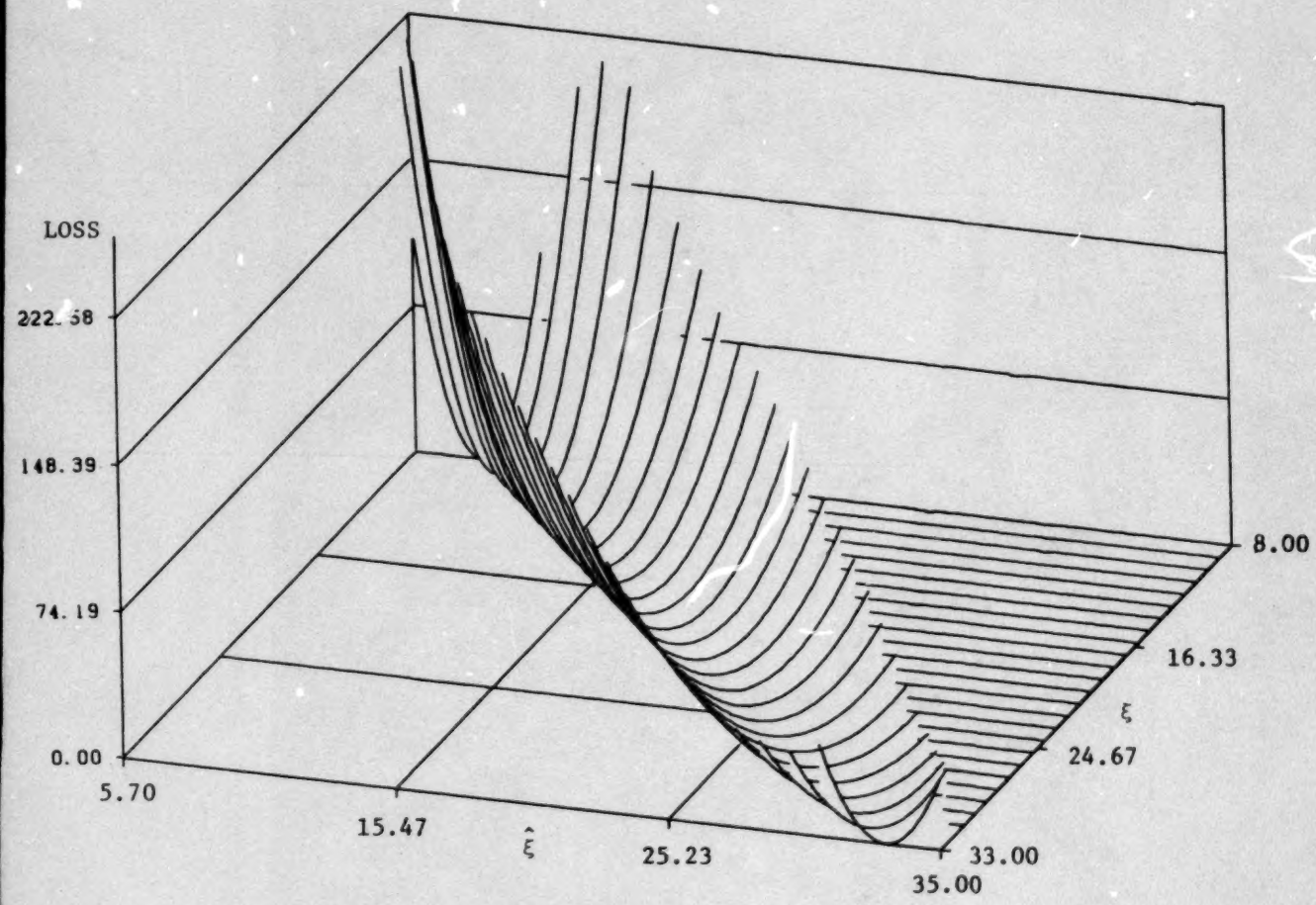

Figure 3. Estimated Loss Function for NJBSCPT, 3EJP, Sentence Sense, N = 19949 , as a function of true score (ξ) and estimated true score ($\hat{\xi}$).

estimated number-right true score. For ease of viewing, both scales at the bottom of the figure run in the opposite direction from the scales at the bottom of Figure 2. This plot is easier to interpret than Figure 2 since we are more accustomed to the number-right score scale than to the θ scale. The plot looks very different from Figure 2 because

1. The loss function for a number-right score of 34 is not shown. The loss function for this score is rather high and would obscure too much of the rest of the figure.
2. A wide range at the high end of the θ scale is compressed into a small range of number-right scores, as shown in the following table:

ξ :	8	10	12	14	16	18	20	22	24	26	28	30	32	34
θ :	-5.2	-3.1	-2.4	-1.9	-1.6	-1.3	-1.0	-.7	-.4	-.2	.1	.5	1.0	2.1

Again, it appears that the test discriminates at high true score levels, where discrimination is not really desired. The loss function at $\xi = 34$ (not plotted) shows a loss of approximately 100 when $\hat{\xi}$ is two standard errors from ξ. For number-right scores of 30 and below, the shape of the loss function seems very appropriate for a competency test, with very high losses attributed to errors of measurement at low score levels.

6. Discussion

In the case of a minimum competency test, the social losses arising from errors of measurement will be high for examinees near the cutting score, which is always near the low end of the score scale. Social losses will be near zero for examinees far from the cutting score, since decisions about these examinees will not be changed by small errors in their scores.

For a college admissions test, it would seem reasonable to expect that errors of measurement in the scores of high ability sutdents will result in relatively high social losses. Somewhat lower social losses should be expected to result from errors in the scores of low ability students.

In the case of grade school tests of 'ability' or of vocabulary, it has sometimes been argued that, to be fair, the standard error of measurement of the test score should be roughly the same for each individual (see, for example, Hulin et al., 1983, p. 90). The first difficulty with this approach is that its implications for test design when the test score is $\hat{\theta}$ are completely different than when the test score is $\hat{\xi}$ or simply the number of right answers. Although equality of standard errors of measurement at all ability levels has strong intuitive appeal, there is no clear way to decide whether this equality should hold on the θ scale, or on the number-right score scale, or on some other scale. It cannot hold simultaneously on two different scales unless one scale is a linear transformation of the other.

In any case, any goal of equal standard errors of measurement at different ability levels is completely incompatible with the goal of minimizing expected social loss due to errors of measurement. If we wish to minimize social loss, we must, other things being equal, mobilize our test development resources so as to measure most accurately at those ability levels where the most people are found. We cannot waste items in order to secure accurate measurement at ability levels where only a few people will be affected, unless, of course, there is a very high loss function at these ability levels. In a word, accuracy of measurement in sparsely populated stretches of the ability range must be sacrificed, other things being equal, in order to obtain more accurate measurement in heavily populated stretches.

As a concrete example, consider a vocabulary test for grade 5 and suppose our test is built to minimize overall expected loss. Suppose also, as might be reasonable for such a test, that the expected loss at a fixed ability level is constant across ability levels, so that, by (12),

$$\mathcal{E}[L(\hat{\theta},\theta)|\theta] = \frac{1}{2}\frac{I^2(\theta)}{g(\theta)}\,\mathcal{E}[(\hat{\theta}-\theta)^2|\theta] = \frac{1}{2}\frac{I^2(\theta)}{g(\theta)}\,\frac{1}{I(\theta)} = K$$

where K is some constant. It follows that

$$\mathrm{Var}(\hat{\theta}|\theta) = \frac{1}{I(\theta)} = \frac{1}{2Kg(\theta)}$$

Since $g(\theta)$ is small for extreme θ, the standard error of measurement, $\sqrt{\text{Var}(\hat{\theta}|\theta)}$, will in this case be very much larger for examinees with extreme θ than for examinees with moderate θ. Thus in this case the goal of equal standard errors of measurement at all ability levels is utterly incompatible with minimizing overall expected loss. This is simply an illustration of the fact that if we wish to minimize overall expected loss, our measurement effort must be concentrated on the sub-ranges of ability that are most highly populated in the target population.

To summarize, in respect to a unidimensional test:

1. Given the loss function, the distribution of ability in a target population, and certain constraints on the available item pool, a method has been described for designing a test that will minimize expected loss.

2. Given a test and also the distribution of ability in the target population, a method has been described for finding the loss function for which this test is an optimally designed test given certain constraints on the available item pool.

3. Minimizing social loss is in general incompatible with equal measurement accuracy across examinees. To minimize social loss, measurement accuracy must be high (other things being equal) over ability ranges that are heavily populated, and relatively low over ranges that are sparsely populated.

Reference Note

Wingersky, M. S., Barton, M. A., & Lord, F. M. LOGIST user's guide. Princeton, N.J.: Educational Testing Service, February 1982.

References

Birnbaum, A. Some latent trait models and their uses in inferring an examinee's ability. Part 5 of F. M. Lord and M. R. Novick, Statistical theories of mental test scores. Reading, Mass.: Addison-Wesley, 1968.

Hulin, C. L., Drasgow, F., & Parsons, C. K. Item response theory. Homewood, Ill.: Dow Jones-Irwin, 1983.

Lord, F. M. Applications of item response theory to practical testing problems. Hillsdale, N.J.: Lawrence Erlbaum Associates, 1980.

DISTRIBUTION LIST

Navy

1 Dr. Ed Aiken
Navy Personnel R&D Center
San Diego, CA 92152

1 Dr. Arthur Bachrach
Environmental Stress Program Center
Naval Medical Research Institute
Bethesda, MD 20014

1 Dr. Meryl S. Baker
Navy Personnel R&D Center
San Diego, CA 92152

1 Liaison Scientist
Office of Naval Research
Branch Office London
Box 39
FPO New York, NY 09510

1 Lt. Alexander Bory
Applied Psychology
Measurement Division
NAMRL
NAS Pensacola, FL 32508

1 Dr. Robert Breaux
NAVTRAEQUIPCEN
Code N-095R
Orlando, FL 32813

1 Dr. Robert Carroll
NAVOP 115
Washington, DC 20370

1 Chief of Naval Education and
Training Liason Office
Air Force Human Resource Laboratory
Flying Training Division
Williams Air Force Base, AZ 85224

1 Dr. Stanley Collyer
Office of Naval Technology
800 N. Quincy Street
Arlington, VA 22217

1 CDR Mike Curran
Office of Naval Research
800 North Quincy Street
Code 270
Arlington, VA 22217

1 Dr. Tom Duffy
Navy Personnel R&D Center
San Diego, CA 92152

1 Mr. Mike Durmeyer
Instructional Program Development
Building 90
NET-PDCD
Great Lakes NTC, IL 60088

1 Dr. Richard Elster
Department of Administrative Sciences
Naval Postgraduate School
Monterey, CA 93940

1 Dr. Pat Federico
Code P13
Navy Personnel R & D Center
San Diego, CA 92152

1 Dr. Cathy Fernandes
Navy Personnel R & D Center
San Diego, CA 92152

1 Dr. John Ford
Navy Personnel R & D Center
San Diego, CA 92152

1 Dr. Jim Hollan
Code 14
Navy Personnel R & D Center
San Diego, CA 92152

1 Dr. Ed Hutchins
Navy Personnel R & D Center
San Diego, CA 92152

1 Dr. Norman J. Kerr
Chief of Naval Technical Training
Naval Air Station Memphis (75)
Millington, TN 38054

1 Dr. Peter Kincaid
Training Analysis & Evaluation Group
Department of the Navy
Orlando, FL 32813

1 Dr. R. W. King
Director, Naval Education
and Training Program
Naval Training Center, Bldg. 90
Great Lakes, IL 60088

1 Dr. Leonard Kroeker
Navy Personnel R & D Center
San Diego, CA 92152

1 Dr. William L. Maloy (02)
Chief of Naval Education and Training
Naval Air Station
Pensacola, FL 32508

1 Dr. Kneale Marshall
Chairman, Operations Research Dept.
Naval Post Graduate School
Monterey, CA 93940

1 Dr. James McBride
Navy Personnel R & D Center
San Diego, CA 92152

1 Dr. William Montague
NPRDC Code 13
San Diego, CA 92152

1 Mr. William Nordbrock
1032 Fairlawn Avenue
Libertyville, IL 60048

1 Library, Code P201L
Navy Personnel R & D Center
San Diego, CA 92152

1 Technical Director
Navy Personnel R & D Center
San Diego, CA 92152

6 Personnel & Training Research Group
Code 442PT
Office of Naval Research
Arlington, VA 22217

1 Special Asst. for Education and
Training (OP-01E)
Room 2705 Arlington Annex
Washington, DC 20370

1 LT Frank C. Petho, MSC, USN
CNET (N-432)
NAS
Pensacola, FL 32508

1 Dr. Bernard Rimland (01C)
Navy Personnel R & D Center
San Diego, CA 92152

1 Dr. Carl Ross
CNET-PDCD
Building 90
Great Lakes NTC, IL 60088

1 Dr. Worth Scanland, Director
CNET (N-5)
NAS
Pensacola, FL 32508

1 Dr. Robert G. Smith
Office of Chief of Naval Operations
OP-987H
Washington, DC 20350

1 Dr. Alfred F. Smode, Director
Training Analysis and Evaluation Group
Department of the Navy
Orlando, FL 32813

1 Dr. Richard Sorensen
Navy Personnel R & D Center
San Diego, CA 92152

1 Dr. Frederick Steinheiser
CNO - OP115
Navy Annex
Arlington, VA 20370

1 Mr. Brad Sympson
Naval Personnel R & D Center
San Diego, CA 92152

1 Dr. Frank Vicino
Navy Personnel R & D Center
San Diego, CA 92152

1 Dr. Edward Wegman
Office of Naval Research (Code 411S&P)
800 North Quincy Street
Arlington, VA 22217

1 Dr. Ronald Weitzman
Code 54 WZ
Department of Administrative Services
U.S. Naval Postgraduate School
Monterey, CA 93940

1 Dr. Douglas Wetzel
Code 12
Navy Personnel R & D Center
San Diego, CA 92152

1 Dr. Martin F. Wiskoff
Navy Personnel R & D Center
San Diego, CA 92152

1 Mr. John H. Wolfe
Navy Personnel R & D Center
San Diego, CA 92152

1 Dr. Wallace Wulfeck, III
Navy Personnel R & D Center
San Diego, CA 92152

Marine Corps

1 Dr. H. William Greenup
Education Advisor (E031)
Education Center, MCDEC
Quantico, VA 22134

1 Director, Office of Manpower Utilization
HQ, Marine Corps (MPU)
BCB, Building 2009
Quantico, VA 22134

1 Headquarters, U. S. Marine Corps
Code MPI-20
Washington, DC 20380

1 Special Assistant for Marine Corps Matters
Code 100M
Office of Naval Research
800 N. Quincy Street
Arlington, VA 22217

1 Dr. A. L. Slafkosky
Scientific Advisor
Code RD-1
HQ, U.S. Marine Corps
Washington, DC 20380

1 Major Frank Yohannan, USMC
Headquarters, Marine Corps
(Code MPI-20)
Washington, DC 20380

Army

1 Technical Director
U.S. Army Research Institute for the Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Mr. James Baker
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Kent Eaton
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Army

1 Dr. Beatrice J. Farr
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Myron Fischl
U.S. Army Research Institute for the Social and Behavioral Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Milton S. Katz
Training Technical Area
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Harold F. O'Neil, Jr.
Director, Training Research Lab
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Commander, U.S. Army Research Institute
ATTN: PERI-BR (Dr. Judith Orasanu)
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Joseph Psotka
ATTN: PERI-IC
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Mr. Robert Ross
U.S. Army Research Institute for the Social and Behavioral Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Robert Sasmor
U.S. Army Research Institute for the Social and Behavioral Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Joyce Shields
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Hilda Wing
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Robert Wisher
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Air Force

1 Air Force Human Resources Laboratory
AFHRL/MPD
Brooks Air Force Base, TX 78235

1 Technical Documents Center
Air Force Human Resources Laboratory
WPAFB, OH 45433

1 U.S. Air Force Office of Scientific Research
Life Sciences Directorate, NL
Bolling Air Force Base
Washington, DC 20332

1 Air University Library
AUL/LSE 76/443
Maxwell AFB, AL 36112

1 Dr. Earl A. Alluisi
HQ, AFHRL (AFSC)
Brooks Air Force Base, TX 78235

1 Mr. Raymond E. Christal
AFHRL/MOE
Brooks AFB, TX 78235

1 Dr. Alfred R. Fregly
AFOSR/NL
Bolling AFB, DC 20332

Air Force

1 Dr. Genevieve Haddad
Program Manager
Life Sciences Directorate
AFOSR
Bolling AFB, DC 20332

1 Dr. T. M. Longridge
AFHRL/OTE
Williams AFB, AZ 85224

1 Dr. Roger Pennell
Air Force Human Resources Laboratory
Lowry AFB, CO 80230

1 Dr. Malcolm Ree
AFHRL/MP
Brooks Air Force Base, TX 78235

1 LT Tallarigo
3700 TCHTW/TTGHR
Sheppard AFB, TX 76311

1 Dr. Joseph Yasatuke
AFHRL/LRT
Lowry AFB, CO 80230

Department of Defense

12 Defense Technical Information Center
Attn: TC
Cameron Station, Building 5
Alexandria, VA 22314

1 Dr. Craig I. Fields
Advanced Research Projects Agency
1400 Wilson Blvd.
Arlington, VA 22209

1 Dr. William Graham
Testing Directorate
MEPCOM/MEPCT-P
Ft. Sheridan, IL 60037

Department of Defense

1 Mr. Jerry Lehnus
HQ MEPCOM
Attn: MEPCT-P
Ft. Sheridan, IL 60037

1 Military Assistant for Training
and Personnel Technology
Office of the Under Secretary of
Defense for Research and Engineering
Room 3D129, The Pentagon
Washington, DC 20301

1 Dr. Wayne Sellman
Office of the Assistant Secretary
of Defense (MRA&L)
2B269 The Pentagon
Washington, DC 20301

1 Major Jack Thorpe
DARPA
1400 Wilson Blvd.
Arlington, VA 22209

Civilian Agencies

1 Dr. Patricia A. Butler
NIE-BRN Bldg., Stop #7
1200 19th Street, NW
Washington, DC 20208

1 Dr. Susan Chipman
Learning and Development
National Institute of Education
1200 19th Street NW
Washington, DC 20208

1 Dr. Arthur Melmed
724 Brown
U.S. Department of Education
Washington, DC 20208

1 Dr. Andrew R. Molnar
Office of Scientific and Engineering
Personnel and Education
National Science Foundation
Washington, DC 20550

Civilian Agencies

1 Dr. Vern W. Urry
Personnel R & D Center
Office of Personnel Management
1900 E Street, NW
Washington, DC 20415

1 Mr. Thomas A. Warm
U.S. Coast Guard Institute
P.O. Substation 18
Oklahoma City, OK 73169

1 Dr. Frank Withrow
U.S. Office of Education
400 Maryland Avenue, SW
Washington, DC 20202

1 Dr. Joseph L. Young, Director
Memory and Cognitive Processes
National Science Foundation
Washington, DC 20550

Private Sector

1 Dr. James Algina
University of Florida
Gainesville, FL 32611

1 Dr. Patricia Baggett
Department of Psychology
University of Colorado
Boulder, CO 80309

1 Dr. Isaac Bejar
Educational Testing Service
Princeton, NJ 08541

1 Dr. Menucha Birenbaum
School of Education
Tel Aviv University
Tel Aviv, Ramat Aviv 69978
ISRAEL

Private Sector

1 Dr. R. Darrell Bock
Department of Education
University of Chicago
Chicago, IL 60637

1 Dr. Robert Brennan
American College Testing Programs
P.O. Box 168
Iowa City, IA 52243

1 Dr. Glenn Bryan
6208 Poe Road
Bethesda, MD 20817

1 Dr. Ernest R. Cadotte
307 Stokely
University of Tennessee
Knoxville, TN 37916

1 Dr. Pat Carpenter
Department of Psychology
Carnegie-Mellon University
Pittsburgh, PA 15213

1 Dr. John B. Carroll
409 Elliott Road
Chapel Hill, NC 27514

1 Dr. Norman Cliff
Department of Psychology
University of Southern California
University Park
Los Angeles, CA 90007

1 Dr. Allan M. Collins
Bolt, Beranek, and Newman, Inc.
50 Moulton Street
Cambridge, MA 02138

1 Dr. Lynn A. Cooper
LRDC
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

Private Sector

1 Dr. Hans Crombag
Education Research Center
University of Leyden
Boerhaavelaan 2
2334 EN Leyden
THE NETHERLANDS

1 Dr. Dattpradad Divgi
Syracuse University
Department of Psychology
Syracuse, NY 33210

1 Dr. Susan Embertson
Psychology Department
University of Kansas
Lawrence, KS 66045

1 ERIC Facility-Acquisitions
4833 Rugby Avenue
Bethesda, MD 20014

1 Dr. Benjamin A. Fairbank, Jr.
McFann-Gray and Associates, Inc.
5825 Callaghan
Suite 225
San Antonio, TX 78228

1 Dr. Leonard Feldt
Lindquist Center for Measurement
University of Iowa
Iowa City, IA 52242

1 Prof. Donald Fitzgerald
University of New England
Armidale, New South Wales 2351
AUSTRALIA

1 Dr. Dexter Fletcher
WICAT Research Institute
1875 S. State Street
Orem, UT 22333

1 Dr. John R. Frederiksen
Bolt, Beranek, and Newman
50 Moulton Street
Cambridge, MA 02138

Private Sector

1 Dr. Janice Gifford
University of Massachusetts
School of Education
Amherst, MA 01002

1 Dr. Robert Glaser
LRDC
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

1 Dr. Bert Green
Department of Psychology
Johns Hopkins University
Charles and 34th Streets
Baltimore, MD 21218

1 Dr. Ron Hambleton
School of Education
University of Massachusetts
Amherst, MA 01002

1 Dr. Paul Horst
677 G Street, #184
Chula Vista, CA 90010

1 Dr. Lloyd Humphreys
Department of Psychology
University of Illinois
Champaign, IL 61820

1 Dr. Jack Hunter
2122 Coolidge Street
Lansing, MI 48906

1 Dr. Huynh Huynh
College of Education
University of South Carolina
Columbia, SC 29208

1 Dr. Douglas H. Jones
10 Trafalgar Court
Lawrenceville, NJ 08648

Private Sector

1 Prof. John A. Keats
Department of Psychology
University of Newcastle
Newcastle, New South Wales 2308
AUSTRALIA

1 Dr. William Koch
University of Texas-Austin
Measurement and Evaluation Center
Austin, TX 78703

1 Dr. Pat Langley
The Robotics Institute
Carnegie-Mellon University
Pittsburgh, PA 15213

1 Dr. Alan Lesgold
Learning R & D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15260

1 Dr. Michael Levine
Department of Educational Psychology
210 Education Building
University of Illinois
Champaign, IL 61801

1 Dr. Charles Lewis
Faculteit Sociale Wetenschappen
Rijksuniversiteit Groningen
Oude Boteringestraat 23
9712GC Groningen
NETHERLANDS

1 Dr. Robert Linn
College of Education
University of Illinois
Urbana, IL 61801

1 Mr. Phillip Livingston
Systems and Applied Sciences Corporation
68111 Kenilworth Avenue
Riverdale, MD 20840

Private Sector

1 Dr. Robert Lockman
Center for Naval Analysis
200 North Beauregard Street
Alexandria, VA 22311

1 Dr. Frederic M. Lord
Educational Testing Service
Princeton, NJ 08541

1 Dr. James Lumsden
Department of Psychology
University of Western Australia
Nedlands, Western Australia 6009
AUSTRALIA

1 Dr. Gary Marco
Stop 31-E
Educational Testing Service
Princeton, NJ 08541

1 Dr. Scott Maxwell
Department of Psychology
University of Notre Dame
Notre Dame, IN 46556

1 Dr. Samuel T. Mayo
Loyola University of Chicago
820 North Michigan Avenue
Chicago, IL 60611

1 Mr. Robert McKinley
American College Testing Programs
P.O. Box 168
Iowa City, IA 52243

1 Dr. Robert Mislevy
711 Illinois Street
Geneva, IL 60134

1 Dr. Allen Munro
Behavioral Technology Laboratories
1845 Elena Avenue, Fourth Floor
Redondo Beach, CA 90277

Private Sector

1 Dr. Alan Nicewander
University of Oklahoma
Department of Psychology
Oklahoma City, OK 73069

1 Dr. Donald A. Norman
Cognitive Science, C-015
University of California, San Diego
La Jolla, CA 92093

1 Dr. Melvin R. Novick
356 Lindquist Center for Measurement
University of Iowa
Iowa City, IA 52242

1 Dr. James Olson
WICAT, Inc.
1875 S. State Street
Orem, UT 84057

1 Dr. Wayne M. Patience
American Council on Education
GED Testing Service, Suite 20
One Dupont Circle, NW
Washington, DC 20036

1 Dr. James A. Paulson
Portland State University
P.O. Box 751
Portland, OR 97207

1 Dr. James W. Pellegrino
Univeristy of California,
Santa Barbara
Department of Psychology
Santa Barbara, CA 93106

1 Dr. Mark D. Reckase
ACT
P.O. Box 168
Iowa City, IA 52243

1 Dr. Lauren Resnick
LRDC
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15261

Private Sector

1 Dr. Thomas Reynolds
University of Texas, Dallas
Marketing Department
P.O. Box 688
Richardson, TX 75080

1 Dr. Andrew Rose
American Institutes for Research
1055 Thomas Jefferson St., NW
Washington, DC 20007

1 Dr. Ernst Z. Rothkopf
Bell Laboratories
Murray Hill, NJ 07974

1 Dr. Lawrence Rudner
403 Elm Avenue
Takoma Park, MD 20012

1 Dr. J. Ryan
Department of Education
University of South Carolina
Columbia, SC 29208

1 Prof. Fumiko Samejima
Department of Psychology
University of Tennessee
Knoxville, TN 37916

1 Dr. Walter Schneider
Psychology Department
603 E. Daniel
Champaign, IL 61820

1 Dr. Lowell Schoer
Psychological and Quantitative
Foundations
College of Education
University of Iowa
Iowa City, IA 52242

1 Dr. Robert J. Seidel
Instructional Technology Group
HUMRRO
300 N. Washington Street
Alexandria, VA 22314

Private Sector

1 Dr. Kazuo Shigemasu
University of Tohoku
Department of Educational Psychology
Kawauchi, Sendai 980
JAPAN

1 Dr. Edwin Shirkey
Department of Psychology
University of Central Florida
Orlando, FL 32816

1 Dr. William Sims
Center for Naval Analysis
200 North Beauregard Street
Alexandria, VA 22311

1 Dr. H. Wallace Sinaiko
Program Director
Manpower Research and Advisory Services
Smithsonian Institution
801 North Pitt Street
Alexandria, VA 22314

1 Dr. Richard Snow
School of Education
Stanford University
Stanford, CA 94305

1 Dr. Kathryn T. Spoehr
Psychology Department
Brown University
Providence, RI 02912

1 Dr. Robert Sternberg
Department of Psychology
Yale University
Box 11A, Yale Station
New Haven, CT 06520

1 Dr. Peter Stoloff
Center for Naval Analysis
200 North Beauregard Street
Alexandria, VA 22311

Private Sector

1 Dr. William Stout
University of Illinois
Department of Mathematics
Urbana, IL 61801

1 Dr. Patrick Suppes
Institute for Mathematical Studies
in the Social Sciences
Stanford University
Stanford, CA 94305

1 Dr. Hariharan Swaminathan
Laboratory of Psychometric and
Evaluation Research
School of Education
University of Massacuusetts
Amherst, MA 01003

1 Dr. Kikumi Tatsuoka
Computer Based Education Research
Laboratory
252 Engineering Research Laboratory
University of Illinois
Urbana, IL 61801

1 Dr. Maurice Tatsuoka
220 Education Building
1310 S. Sixth Street
Champaign, Il 61820

1 Dr. David Thissen
Department of Psychology
University of Kansas
Lawrence, KS 66044

1 Dr. Douglas Towne
University of Southern California
Behavioral Technology Labs
1845 S. Elena Avenue
Redondo Beach, CA 90277

1 Dr. Robert Tsutakawa
Department of Statistics
University of Missouri
Columbia, MO 65201

Private Sector

1 Dr. V. R. R. Uppuluri
Union Carbide Corporation
Nuclear Division
P.O. Box Y
Oak Ridge, TN 37830

1 Dr. David Vale
Assessment Systems Corporation
2233 University Avenue
Suite 310
St. Paul, MN 55114

1 Dr. Kurt Van Lehn
Xerox PARC
3333 Coyote Hill Road
Palo Alto, CA 94304

1 Dr. Howard Wainer
Educational Testing Service
Princeton, NJ 08541

1 Dr. Michael T. Waller
Department of Educational Psychology
University of Wisconsin
Milwaukee, WI 53201

1 Dr. Brian Waters
HUMRRO
300 North Washington
Alexandria, VA 22314

1 Dr. Phyllis Weaver
2979 Alexis Drive
Palo Alto, CA 94304

1 Dr. David J. Weiss
N660 Elliott Hall
University of Minnesota
75 East River Road
Minneapolis, MN 55455

1 Dr. Keith T. Wescourt
Perceptronics, Inc.
545 Middlefield Road
Suite 140
Menlo Park, CA 94025

Private Sector

1 Dr. Rand R. Wilcox
University of Southern California
Department of Psychology
Los Angeles, CA 90007

1 Dr. Wolfgang Wildgrube
Streitkraefteamt
Box 20 50 03
D-5300 Bonn 2
WEST GERMANY

1 Dr. Bruce Williams
Department of Educational Psychology
University of Illinois
Urbana, IL 61801

1 Dr. Wendy Yen
CTB/McGraw-Hill
Del Monte Research Park
Monterey, CA 93940